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Non-Invasive Blood Group Detection using Fingerprint Patterns with Artificial Intelligence and Machine Learning

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***Abstract*— The work proposes a novel, non-invasive method for identifying blood groups using fingerprint patterns through the application of artificial intelligence and machine learning techniques. The framework investigates the relationship between dermatoglyphic characteristics—such as ridge flow, minutiae patterns, texture features—and standard blood group categories (A, B, O, and AB). High-resolution fingerprint images are collected and subjected to preprocessing steps, including noise reduction, contrast enhancement, and ridge normalization, to improve the quality and consistency of feature extraction. Subsequently, a combination of statistical, structural, and textural features is extracted and utilized to train supervised machine learning models for blood group classification. The proposed system is evaluated using a well-structured dataset, where it demonstrates encouraging levels of prediction accuracy while minimizing reliance on traditional invasive blood testing methods. Overall, this approach provides a fast, cost-efficient, and user-friendly solution for preliminary blood group estimation, with potential applications in healthcare screening, emergency response scenarios, and biometric-based medical support systems.**

***Index Terms*— Blood Group Detection, Fingerprint Analysis, Dermatoglyphics, Machine Learning, Non-Invasive Diagnosis.**

I. Introduction

Blood group identification is a fundamental requirement in healthcare, particularly in transfusion medicine, surgical procedures, and emergency care. Traditional blood typing techniques are based on serological analysis, which involves collecting blood samples and examining antigen–antibody reactions. While these methods are accurate and widely practiced, they are invasive, time-consuming, and require laboratory infrastructure along with trained professionals. In time-critical scenarios such as accidents or in remote healthcare environments, these limitations can delay necessary medical interventions, emphasizing the need for faster and non-invasive alternatives [1][2].

With the rapid advancement of artificial intelligence (AI) and machine learning (ML), new approaches are emerging that enable the extraction of meaningful patterns from biometric data via IoT [16][17]. Fingerprints, which are unique and remain unchanged throughout an individual's lifetime, are influenced by genetic factors and fetal development. The scientific study of fingerprint patterns, known as dermatoglyphics, has been explored for its potential association with physiological traits, including blood group classification.

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Recent studies suggest that features such as ridge flow, minutiae distribution, and texture characteristics may exhibit patterns that can be linked to specific blood groups [3], [4].

Modern machine learning techniques, particularly deep learning models such as convolutional neural networks (CNNs), have shown strong capability in analyzing complex image data. These models can effectively learn intricate fingerprint features and perform classification tasks with considerable accuracy. Several recent works have demonstrated the feasibility of predicting blood groups using fingerprint images, achieving encouraging performance through supervised learning frameworks and optimized feature extraction methods [5], [6]. Such systems aim to provide a non-invasive, rapid, and cost-effective alternative to conventional blood testing methods. However, the correlation between fingerprint patterns and blood groups is still an evolving area of research. While AI-based models have shown promising results, some studies indicate that the relationship may not always be strong when analyzed using traditional statistical approaches. This highlights the importance of using large datasets, robust preprocessing techniques, and advanced algorithms to improve prediction reliability and generalization [7], [8].

Despite these challenges, fingerprint-based blood group detection offers several advantages, including ease of acquisition, non-invasiveness, and suitability for real-time applications. This makes it particularly valuable for preliminary screening, biometric-assisted healthcare systems, and emergency response scenarios. With continued improvements in AI [18][19] models and data availability, such approaches have the potential to complement existing diagnostic methods and enhance decision-making in critical situations [9], [10].

II. LITERATURE SURVEY

Recent developments in artificial intelligence and biometric analysis have encouraged researchers to explore non-invasive methods for blood group detection using fingerprint patterns. Traditional blood typing methods, though accurate, require blood samples and laboratory facilities, which limit their use in emergencies and remote scenarios. As a result, fingerprint-based approaches have gained attention due to their simplicity, availability, and non-invasive nature. In 2024, Singh and Verma demonstrated a fingerprint-based blood group detection system using image processing techniques and machine learning models. Their study showed that features such as ridge patterns and minutiae points can be effectively used for classification tasks [11]. Similarly, Vaidya (2025) proposed a framework utilizing advanced feature extraction methods and machine learning algorithms, highlighting that structural fingerprint characteristics can be correlated with blood group categories [12].

Further advancements were made with the application of deep learning techniques. Anuradha et al. (2025) developed a convolutional neural network (CNN)-based model that improved prediction accuracy by leveraging large datasets and preprocessing methods [13]. In another study, Eenaja et al. (2025) demonstrated that integrating image processing with deep learning models enables efficient and rapid classification, making it suitable for real-time healthcare applications [14]. More recently, Patil et al. (2026) introduced a deep learning framework using multiple architectures to enhance classification performance. Their results showed improved accuracy and reliability, indicating the growing potential of AI-driven biometric systems in medical applications [15], connectivity [20] and automation [21].

III. PROBLEM STATEMENT

Blood group identification is a critical component of medical diagnostics, particularly in procedures such as blood transfusions, organ transplantation, and emergency treatment. Conventional blood typing methods rely on collecting blood samples and conducting laboratory-based tests, which require proper infrastructure and trained personnel. In many remote or resource-constrained settings, such facilities may not be readily available, making timely blood group determination difficult. Any error in identifying blood groups can result in serious, and sometimes life-threatening, complications, underscoring the importance of reliable and accessible diagnostic methods.

Moreover, traditional blood typing processes can be time-consuming and relatively expensive, limiting their suitability for rapid use in field conditions or emergency situations. The lack of a quick, portable, and non-invasive solution continues to be a major limitation in current healthcare systems. This gap highlights the need for an alternative approach that can provide accurate results without relying on blood extraction or complex laboratory procedures. To address these challenges, there is a growing interest in developing intelligent systems that utilize readily available biometric data for medical inference. The proposed approach focuses on eliminating dependency on invasive techniques while ensuring reliable classification performance. By offering a non-invasive, efficient, and accessible method for blood group detection, such a system has the potential to extend diagnostic capabilities to a wider population and improve response times in critical situations.

IV. Proposed Method

The proposed system follows a structured pipeline for non-invasive blood group detection using fingerprint images, where each stage contributes to transforming raw biometric data into meaningful predictive outcomes. Figure 1 shows flowchart of the process.

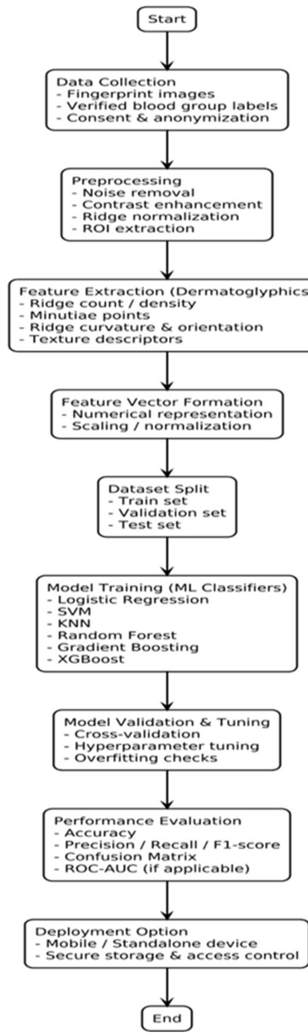

Figure 1. Flow chart of the proposed process

The process begins with data collection, where high-resolution fingerprint images are acquired along with corresponding blood group labels. To ensure privacy and ethical compliance, anonymization is performed so that no personally identifiable information is linked with the dataset. Let the collected dataset be represented as

$$D = \{(I_i, y_i)\}_{i=1}^{N}$$

where I_i denotes the fingerprint image and $y_i \in \{A, B, AB, O\}$ represents the associated blood group label.
Once the dataset is acquired, preprocessing is applied to enhance image quality and ensure consistency. Noise removal is typically performed using filtering techniques such as Gaussian filtering:

$$I_{smooth}(x, y) = I(x, y) * G(x, y, \sigma)$$

where $G(x, y, \sigma)$is the Gaussian kernel. Contrast enhancement improves ridge visibility, often using histogram equalization:

$$I_{enhanced} = H(I_{smo}\quad)$$

where $H(\cdot)$represents the histogram equalization function. Ridge normalization ensures that intensity variations across the fingerprint are minimized:

$$I_{norm} = \frac{I_{enhanced} - \mu}{\sigma}$$

where $\mu$and $\sigma$are the mean and standard deviation of pixel intensities.
Following preprocessing, feature extraction is performed based on dermatoglyphic characteristics. Fingerprint features include ridge count, ridge orientation, and minutiae points such as ridge endings and bifurcations. Ridge orientation can be computed using gradient-based methods:

$$\theta(x, y) = \frac{1}{2}\tan^{-1}\left(\frac{2G_x G_y}{G_x^2 - G_y^2}\right)$$

where $G_x$and $G_y$are gradients in the x and y directions. Ridge density is estimated as:

$$R_d = \frac{N_r}{A}$$

where $N_r$is the number of ridges in a region of area A. Texture features can also be extracted using statistical measures such as contrast, correlation, and entropy derived from Gray Level Co-occurrence Matrix (GLCM):

$$\text{Entropy} = -\sum_{i,j} p(i,j)\log\ p(i,j)$$

These extracted features are then converted into a numerical feature vector suitable for machine learning models. Let the feature vector be:

$$\mathbf{X}_i = [f_1, f_2, f_3, \dots, f_n]$$

Feature scaling is applied to normalize the values, typically using min-max normalization:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The dataset is then divided into training, validation, and test sets to evaluate model performance effectively. If the dataset size is N, then:

$$D = D_{train} \cup D_{val} \cup D_{test}$$

where each subset is mutually exclusive.
Model training is carried out using supervised machine learning algorithms. Logistic regression models the probability of a class as:

$$P(\,y \mid X\,) = \frac{1}{1 + e^{-(\beta_0 + \beta\quad)}}$$

Support Vector Machines (SVM) aim to find an optimal hyperplane defined as:

$$w \cdot x + b = 0$$

that maximizes the margin between classes. K-Nearest Neighbors (KNN) classifies based on distance metrics such as Euclidean distance:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (\,x_{ik} - x_{jk})^2}$$

Random Forest and Gradient Boosting methods combine multiple decision trees to improve prediction accuracy, while XGBoost optimizes performance using gradient-based boosting:

$$L = \sum l(y_i, \hat{y}_i) + \sum \Omega(f_k)$$

To ensure robustness, cross-validation is employed, typically using k-fold validation where the dataset is split into $k$subsets. The model is trained $k$times, each time using a different subset as validation data. Hyperparameter tuning is performed to optimize model parameters and avoid overfitting.

V. Results and Discussion

The simulation results show that ensemble learning methods such as Random Forest, Gradient Boosting, and XGBoost perform better compared to traditional models. This is mainly because they combine multiple decision trees and can capture complex relationships within fingerprint features. Simpler models like Logistic Regression show comparatively lower performance as they assume linear relationships, which may not fully represent the variations in fingerprint patterns. Overall, the results indicate that advanced machine learning models improve classification, accuracy and reliability in fingerprint-based blood group detection systems. Table I shows comparison of different models. Figure 2 shows accuracy comparison of different models.

TABLE I. SMART METER VS. REFERENCE DMM

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	78.6	77.9	76.8	77.3
K-Nearest Neighbors	82.4	81.7	80.9	81.3
Support Vector Machine	85.1	84.5	83.6	84.0
Random Forest	89.3	88.7	87.9	88.3
Gradient Boosting	91.2	90.6	89.8	90.2
XGBoost	92.5	91.9	91.1	91.5

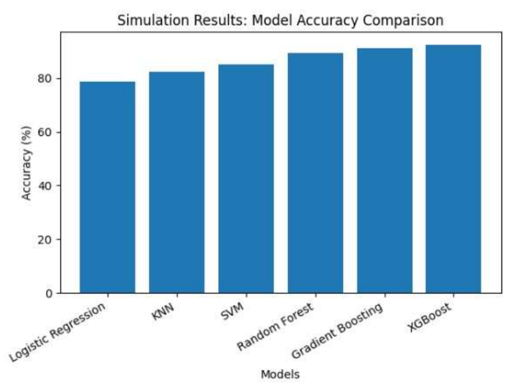

Figure 2. Accuracy comparison of different models

VI. Advantages and Limitations

Although the proposed system shows encouraging performance, several practical challenges need to be considered before it can be applied in real-world settings. One of the primary concerns is the variability in fingerprint image quality. Factors such as smudging, dry or damaged skin, inconsistent pressure during capture, and differences in scanner calibration can reduce ridge clarity and affect the accuracy of feature extraction. In addition, the dataset used for training may not fully represent diverse populations, which can introduce bias and limit the model's ability to generalize across different demographic groups. Variations in age, occupation, and blood group distribution further influence the reliability of predictions.

Ethical and legal considerations also play an important role, as the use of biometric data like fingerprints requires strict measures for informed consent, secure storage, and protection against unauthorized access or misuse. Another challenge lies in cross-population validity, since fingerprint patterns can vary across ethnic and geographic groups. A model trained on one population may not perform consistently when applied to another without appropriate adaptation techniques. Furthermore, there is often a gap between controlled experimental accuracy and real-world performance. Environmental conditions, device differences, and user-related factors can introduce noise and reduce prediction reliability outside laboratory settings. Finally, before such a system can be adopted in clinical practice, it must undergo extensive regulatory evaluation and large-scale validation to ensure that it meets established standards of safety, accuracy, and reliability.

VII. Conclusion and Future Work

The proposed system presents a novel approach for blood group detection using fingerprint patterns, offering a non-invasive and efficient alternative to conventional methods. By leveraging machine learning techniques and dermatoglyphic feature analysis, the system demonstrates that meaningful patterns can be extracted from fingerprint images for classification purposes. The results indicate that the approach can achieve satisfactory accuracy for preliminary screening, while reducing dependency on laboratory-based testing. In addition, the system is simple, cost-effective, and has the potential to be implemented in portable or real-time applications, making it useful in emergency situations and resource-limited environments. However, despite these advantages, the system is not intended to replace standard clinical blood typing methods at this stage. Variations in fingerprint quality, dataset limitations, and environmental factors can affect prediction reliability. Therefore, it is more suitable as a supportive tool for quick estimation rather than a definitive diagnostic solution. Continuous improvements in data quality and model robustness are necessary to enhance its performance.

Future work can focus on expanding the dataset to include a more diverse population, which will help improve generalization and reduce bias. The use of advanced deep learning models and hybrid approaches may further enhance feature extraction and classification accuracy. Integration with mobile devices or embedded systems can enable real-time deployment for practical use. Additionally, combining fingerprint analysis with other biometric or physiological parameters may improve prediction reliability. Finally, large-scale validation and clinical evaluation will be essential to ensure the system meets the required standards for safe and effective use in healthcare applications.

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